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Research article

# Ecological vulnerability assessment for ecological conservation and environmental management

Li He [a], Jing Shen [a, b, *], Yang Zhang [b]

[a] School of Renewable Energy, North China Electric Power University, Beijing 102206, China
[b] Resources and Environmental Research Academy, North China Electric Power University, Beijing 102206, China

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ABSTRACT

Identifying ecological vulnerable regions is a significant aspect in ecological conservation and environmental management. This paper presents a first attempt to provide a prototype framework that can assess ecological vulnerability and evaluate potential impacts of natural, social, economic, environmental pollution, and human health elements on ecological vulnerability with integrating spatial analysis of Geographic Information System (GIS) method and multi-criteria decision analysis (MCDA). A general ecological vulnerability index was constructed to describe the vulnerability status in an ecological hotspot of China. The assessment results of this study confirm the poor ecological vulnerability in China that only 1.32% of the China's population lives in not vulnerable ecosystem. A very high percentage (98.68%) of Chinese with 1.34 billion people lives in vulnerable and highly vulnerable area. This situation is mainly caused by increasing population pressure, exhausted nature resources, extensive economic growth, severe environmental pollution, insufficient environmental protection investment, and accelerating population aging. The spatial comparison indicates that spatial disparity existed in China with the central and northwestern provinces showing higher ecological vulnerability than the northeastern and southern provinces. The results of ecological vulnerability assessment can support effective guidance for mid- or long-term ecologic management. The developed framework can be replicated at different spatial and temporal scales using context-specific datasets to support ecological managers and government with decision-making. With available robust climate change models, future research might incorporate climate change into the ecological vulnerability framework.

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## 1. Introduction

The global and regional eco-system is experiencing unprecedented press and deterioration due to climate change, economy development and humankind activities (Hua et al., 2015; Mitchell et al., 2015; Farley and Voinov, 2016; Virapongse et al., 2016; Blanco et al., 2017; Liang et al., 2017a, 2017b; Chen et al., 2016; Li et al., 2017; He et al., 2017; Chen et al., 2017). Ecological vulnerability assessment is a useful tool to help decision makers understand the various impacts of natural and factitious elements on ecosystem. Under this circumstance, evaluating the ecological vulnerability is necessary to make implications for ecological conservation and environmental management.

Vulnerability is an indicator that integrates multiple multimensional and multivariate attributes (Gonzalez et al., 2010; Chuvieco et al., 2014; Maru et al., 2014; Sugden et al., 2014; Absar and Preston, 2015; Rogers and Xue, 2015; Buotte et al., 2016; Rebolledo et al., 2016; Stevenazzi et al., 2017). As the concept of ecological vulnerability is yet to be fully expounded, the development of vulnerability indices should be conducted at smaller scales and must be context-specific (Heltberg et al., 2009; Sietz et al., 2011; Schwarz et al., 2011; Tubi et al., 2012; Beroya-Eitner, 2016). Therefore, it's a challenge to identify those indicators that can capture ecological vulnerability attribute from the diverse and often incommensurate data. Compared to ecological vulnerability assessment, the vulnerability assessment of ecosystem services is more common. For example, Qiu et al. (2015) assessed the vulnerability of ecosystem services driven by urbanization in China with considering of 16 ecological and socioeconomic variables within an Exposure-Sensitivity-Capacity framework. But it's obvious that vulnerability of ecosystem itself is different with that

* Corresponding author. School of Renewable Energy, North China Electric Power University, Beijing 102206, China.
*E-mail address:* 1132102043@ncepu.edu.cn (J. Shen).

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of ecosystem services. Shen et al. (2016) employed a vulnerability paradigm that contained natural, human, economic, and social elements to assess the vulnerability of four ecosystem receptors (human health, groundwater, surface water, and atmospheric environment) separately in the case study of Beijing, China, but not with an integrated indicator that can straightly show the general ecological vulnerability. Wu et al. (2007) applied an assessment method that considered net primary productivity (NPP), length of growing season, and aridity index as assessment indicators to evaluate the impact of climate change on eco-environment in China under the B2 climate scenario from Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000) of Intergovernmental Panel on Climate Change (IPCC). However, impacts of social and human activity on ecosystem vulnerability were not taken into account in this method. Overall, few studies have focused on evaluating the vulnerability of eco-environment itself that simultaneously considers natural, social, economic, environmental pollution, and human health elements in an ecological vulnerability assessment framework.

As the largest developing country in the world, the eco-environment problem in China is not only our country's focus, but also the hot topic in the worldwide. China has been experiencing rapid economy growth and urbanization with average annual growth rate of 9% in Gross domestic product (GDP) in recent 20 years. However, China's economy has shown uneven regional growth that the coastal regions of eastern China represent more rapid economic growth than that in the other regions. Non-synchronized development of private firms and industrial structure cause the regional disparity. In 2013, China became the second largest global economy according to purchasing power parity and GDP. The urbanization rate has increased into 56.1% in 2015 from 10.64% of 1949. However, the rapid economy growth and urbanization lead to severe ecological problems, such as atmospheric pollution, water contamination, waste pollution, forest deficit, water and soil loss, desertification, and accelerated extinction of biologic species. These ecological problems have seriously affected human health and economic development. The estimation from Chinese Academy of Sciences (CAS) indicated that the economic loss from environmental pollution and ecological destruction in China occupies 15% of the GDP, but the GDP growth is only 7%. This situation indicates that ecological problems may seriously restrict sustainable development and economic development achievements. Therefore, it's an urgent and indispensable task to evaluate ecological vulnerability in China. However, little research has focused on ecological vulnerability assessment in China at a provincial level because of construction difficulty of ecological vulnerability assessment frame and data limits.

The purpose of this paper is to integrate natural, social, economic, environmental pollution, and human health elements within an ecological vulnerability assessment framework that combines spatial analysis of Geographic Information System (GIS) method and multi-criteria decision analysis (MCDA). 15 sub-parameters reflected natural and anthropogenic elements are selected to capture ecological vulnerability attribute and then divided into four groups: ecological situations, ecological infrastructure, environmental situations, and human health. Therefore, a general ecological vulnerability index was constructed to describe the vulnerability status in an ecological hotspot of China. The constructed ecological vulnerability assessment framework will be expected to answer the following three questions: 1) how's the general ecological vulnerability in China? 2) Which provinces in China are the most vulnerable to the increasing ecological problems and anthropogenic activities? And 3) what effective environmental management and protection implications are demanded to sustain and improve the eco-environment capacity?

## 2. Methods and data source

Ecological vulnerability can be defined as 'the ability of ecosystems to absorb changes of state variables, driving variables, and parameters, and still persist'. It is affected by internal and external factors. The developed ecological vulnerability assessment methodology in this paper is proposed by aggregating the MCDA and spatial analysis of GIS. More specifically, the MCDA method can manage data from multiple sources and determine the weight of each attribute. The GIS is applied for spatial analysis and achieving general ecological vulnerability map. There are five steps in the ecological vulnerability assessment framework, as shown in Fig. 1:

(1) indices selection and description;
(2) ecological vulnerability attributes normalization;
(3) weights determination by MCDA;
(4) integration of general ecological vulnerability;
(5) general ecological vulnerability map drawing by GIS.

### 2.1. Indices selection and description

Ecological vulnerability assessment is a complicated process. For now, there is no international recognized standard or rule to stipulate how many and what parameters should be selected to capture ecological vulnerability attribute. In order to select the evaluated indices with the smallest scale and the most representativeness, 15 representative indices reflected natural and anthropogenic elements are selected and divided into four groups: ecological situations, ecological infrastructure, environmental situations, and human health. The definitions and data sources of the 15 indices are represented in Appendix A.

### 2.2. Ecological vulnerability attributes normalization

To make these 15 indices comparable, the original data are normalized into a unified dimension, in a range from 0 to 1. This process is accomplished according to the class boundaries and normalization scores shown in Appendix A. The selection of the indices' classes and matching normalization scores are supported by Chenery structural transformation model (Chenery and Syrquin, 1975), the world's population distribution, Falkenmark Water Stress Indicator (Falkenmark et al., 1989), Technical Criterion for Ecosystem Status Evaluation (HJ 192-2015) (MEP PRC, 2015a,b), Environmental Quality Standard for Surface Water (MEP PRC, 2011), Ambient Air Quality Standards (MEP PRC, 2012), and 5 experts.

### 2.3. Weights determination

MCDA is a multi-criteria decision making tool to decompose a problem into a hierarchical structure. It has been widely applied in environmental risk assessment (Topuz and van Gestel, 2016), ecological impact assessment (Liu et al., 2015), sustainable development planning (Quaddus and Siddique, 2001), soil characterization (López et al., 2008), regional management of species resilience (Fuentes et al., 2013), regional climate change impact (Yin and Cohen, 1994), household vulnerability assessment (Eakin and Bojórquez-Tapia, 2008), groundwater management (Ren et al., 2016), atmospheric vulnerability assessment (Zhang et al., 2016), and many other fields. Analytical hierarchy process (AHP) is one of the most widely used MCDA tool. In our developed ecological vulnerability assessment, the AHP technique is applied to determine weights of the selected indices. This part contains six steps as following (Saaty, 1980; Saaty and Vargas, 2001; Nguyen et al., 2016):

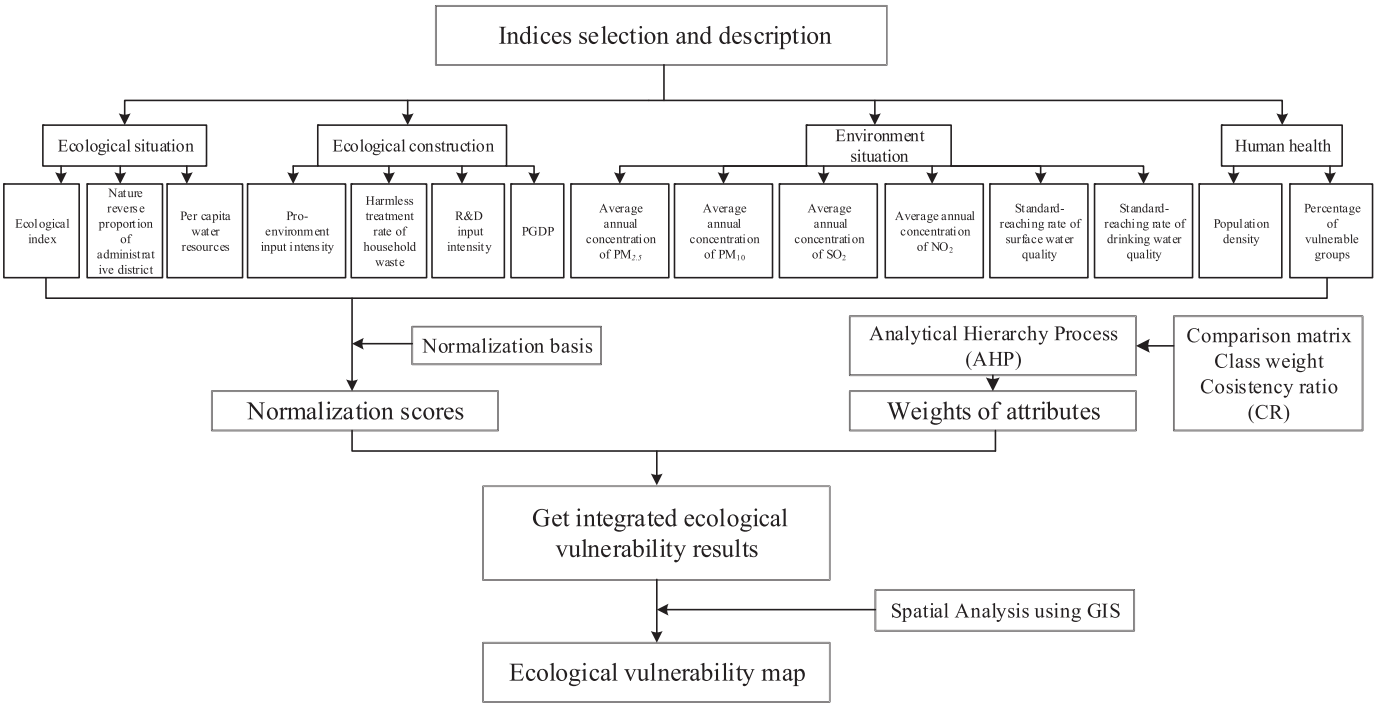


**Fig. 1.** Flow chart of the ecological vulnerability assessment framework.

(1) Deconstruct the decision-making problem into a hierarchical structure. The objective layer is 'ecological vulnerability', which is then deconstructed into the second layer consisting of ecological situation, ecological infrastructure, environmental situation, and human health. Finally, the second layer is further deconstructed into the third layer with corresponding attributes.

(2) Make decision tables for the hierarchical decomposition in each layer with pair-wise comparisons. A preference scaling approach is executed in the pair-wise comparisons with 17 scales numbers: 9, 8, 7, … , 2, 1, 1/2, …,1/7, 1/8, 1/9, where 9 means that one attribute is the most important for the object relative to another. 1means that the contributions of two attributes are equal to the objective layer, and so on down to 1/9, the least important.

(3) Make judgment matrices for the object layer and second layer with the scales numbers from step 2, respectively. In the judgment matrix, 1 is the value of diagonal. If the *i*th row is more important than the *j*th column, than the value of (*i, j*) is more than 1, otherwise the *j*th column is more important than the *i*th row. Meanwhile, the value of (*j, i*) in the matrix is the reciprocal of that in (*i, j*).

(4) Determine weight for each attribute by the largest eigenvalue ($\lambda_{max}$) of the judgment matrix as shown in Eq. (1) (Saaty and Vargas, 2001):

$$\lambda_{max} = \frac{\sum_{i=1}^{n} i\left[\sum_{j=1}^{n}(a_{ij}w_j/w_i)\right]}{n} \quad (1)$$

(5) Estimate the consistency of the judgment matrix by consistency ratio (CR). The CR is related to consistency index (CI) and random index (RI) by Eq. (2) (Saaty and Vargas, 2001):]

$$CR = \frac{CI}{RI} \quad (2)$$

where the CI is calculated by Eq. (3):

$$CI = (\lambda_{max} - n)(n-1) \quad (3)$$

and the RI is a random matrix defined as the average value of resulting consistency index depending on the order of the matrix. The value of CR is suggested to be less than 0.1, which verifies the reasonable consistency of the judgment matrix.

(6) Aggregate the local weight of each attribute to achieve the general weight of corresponding group index.

### 2.4. Integration of general ecological vulnerability

This step aims to aggregate the four group indices into general ecological vulnerability (EV) value. In this study, the EV is achieved based on the normalization values of all parameters and their corresponding weights as shown in Eq. (4):

$$EV = \sum(G_1 \times W_1 + G_2 \times W_2 + G_3 \times W_3 + G_4 \times W_4) \quad (4)$$

where $G_i$, $i = 1, 2, 3, 4$ are global values for ecological situation, ecological infrastructure, environmental situation, and human health, respectively, and $W_i$, $i = 1, 2, 3, 4$ are the corresponding weights for the four group indices as shown in Table 1. $G_i$ are calculated by Eq. (5):

$$G_i = \sum_{i=1}^{n} E_i W_i \quad (5)$$

where $E_i$ is the normalization value of each attribute from chapter

**Table 1**
Weights of group elements and attribute indices.

| Object | Group indices ($G_i$) | Global weight ($W_i$) | No. | Parameters ($E_i$) | Local weight ($w_i$) |
|---|---|---|---|---|---|
| Ecological vulnerability | Ecological situation ($G_1$) | 0.3905 | E1 | Ecological index | 0.2232 |
| | | | E 2 | Nature reserve proportion of administrative district | 0.0558 |
| | | | E 3 | Per capita water resources | 0.1116 |
| | Ecological infrastructure ($G_2$) | 0.2761 | E 4 | Pro-environment input intensity | 0.129 |
| | | | E 5 | Innocuous disposal rate of municipal waste | 0.0442 |
| | | | E 6 | R&D input intensity | 0.0264 |
| | | | E 7 | PGDP | 0.0765 |
| | Environmental situation ($G_3$) | 0.1953 | E 8 | Average annual concentration of $PM_{2.5}$ | 0.0557 |
| | | | E 9 | Average annual concentration of $PM_{10}$ | 0.0316 |
| | | | E10 | Average annual concentration of $SO_2$ | 0.0143 |
| | | | E11 | Average annual concentration of $NO_2$ | 0.0143 |
| | | | E12 | Qualified rate of surface water quality | 0.0091 |
| | | | E13 | Qualified rate of drinking water quality | 0.0703 |
| | Human health ($G_4$) | 0.1381 | E14 | Population density | 0.092 |
| | | | E15 | Percentage of vulnerable groups | 0.046 |

**Table 2**
Judgment table of five ecological vulnerability classes with corresponding normalized score intervals.

| Vulnerability classes | Description | Normalized score interval |
|---|---|---|
| 1 | Not vulnerable | 0.0–0.2 |
| 2 | Somewhat Vulnerable | 0.2–0.4 |
| 3 | Vulnerable | 0.4–0.6 |
| 4 | Highly vulnerable | 0.6–0.8 |
| 5 | Extremely vulnerable | 0.8–1.0 |

2.2, $w_i$ is the local weight of each attribute shown in Table 1, $n$ is the number of parameters in group $G_i$, and $i = 1, 2, 3, \ldots, n$.

### 2.5. General ecological vulnerability map drawn by GIS

For a more visualized judgment, five ecological vulnerability classes are set with corresponding normalized score intervals, as shown in Table 2. The last step of the ecological vulnerability assessment is to match the value of EV from Eq. (4) with this judgment table and receive the vulnerability class. Higher class means higher vulnerability and lower class means lower vulnerability with higher stability of the researched ecosystem. The final step is to import the vulnerability class results into GIS software and achieve ecological vulnerability map. Thus, decision makers can visually see a map with ecological vulnerability results in different regions.

## 3. Results

In order to verify the reliability and consistency of the developed framework, we applied it to evaluate the ecological vulnerability in 31 provinces of China from 2012 to 2014. According to the ecological vulnerability assessment method shown in Chapter 2, the first step is to select 15 parameters and define them. Secondly, data of the 15 parameters are collected and normalized into a unified dimension belonging to [0, 1] basing on Appendix A. If data is null or uncollected, the normalization score is set as 1. These normalized scores of 15 indices are one of the input data in the vulnerability integration process. The other essential input data is the weight of each index derived from the AHP method. After receiving the normalization scores of 15 sub-indices and corresponding weights, the ecological vulnerability results of 31 provinces in China can be aggregated with these two inputs. Then the ecological vulnerability results are matched with Table 2 to get the vulnerability classes. The vulnerability class consequences are finally imported into GIS to get the general ecological vulnerability maps of China for spatial and temporal analysis.

### 3.1. Ecological vulnerability

The general ecological vulnerability maps of 31 provinces in China from 2012 to 2014 are shown in Fig. 2(a, b, c), respectively. It can be seen that all the ecological assessment results of the 31 provinces range from the level of somewhat vulnerable to highly vulnerable (0.2–0.8), but none shows not vulnerable (0–0.2) or extremely vulnerable (0.8–1) ecological vulnerability. The general ecological vulnerability of China, obtained from the average ecological vulnerability scores of the 31 provinces, are 0.561, 0.577, and 0.498 in the three years, respectively, showing at vulnerable level (0.4–0.6). In 2014, 3, 23, and 5 provinces among the 31 provinces present the ecological vulnerability at somewhat vulnerable (0–0.2), vulnerable (0.4–0.6), and highly vulnerable (0.6–0.8) level, respectively. According to statistics analysis for 2014, only 1.32% of the China's population lives in not vulnerable ecosystem. A very high percentage (98.68%) of Chinese with 1.34 billion people lives in vulnerable and high vulnerable provinces.

For a spatial comparison, Fig. 2 shows obviously regional disparity of ecological vulnerability in China. More specifically, the central and northwestern regions show higher ecological vulnerability than the northeastern and southern regions. The temporal comparison from 2012 to 2014 indicates that 6 provinces turn better. 1 province (Hainan) changes from vulnerable to somewhat vulnerable level, accounting for 0.35% of the national territorial area. Meanwhile, 5 provinces turn from highly vulnerable to vulnerable level, occupying for 10.25% of the national territorial area. There is only one province turn worse. Beijing's ecological vulnerability changes from vulnerable to highly vulnerable, accounting for 0.17% of the territorial land.

### 3.2. Sub-parameter impact

Evaluating the impacts of each sub-parameter is helpful to make ecological conservation and environmental management suggestions. Meanwhile, decision makers can better understand the relationships between natural, human, economic, social element and general vulnerability situation. The normalized scores of the 15 sub-parameters, within the four group indices including ecological situation, ecological infrastructure, environmental situation, and human health, are classified into five levels namely not vulnerable (0–0.2), somewhat vulnerable (0.2–0.4), vulnerable (0.4–0.6), highly vulnerable (0.6–0.8), and extremely vulnerable (0.8–1). Then the proportional distributions of the five levels for each index

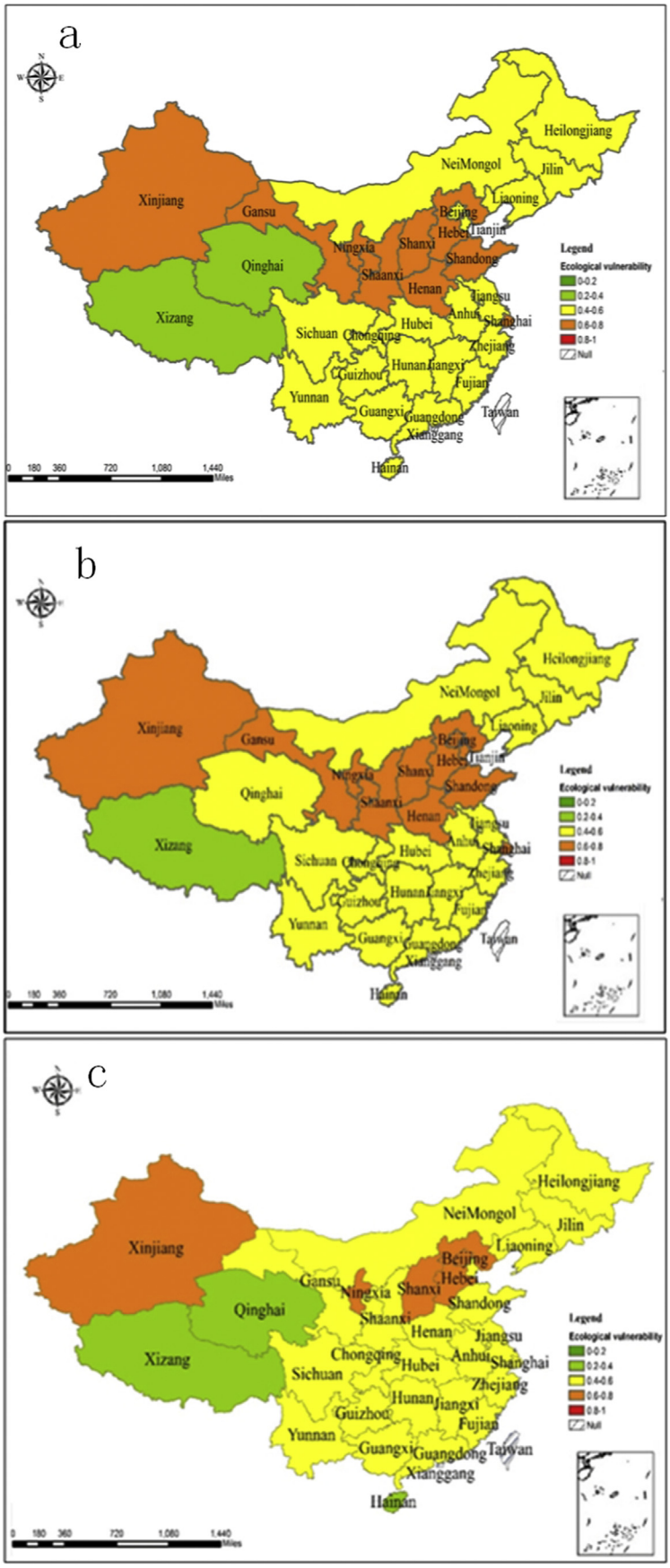


**Fig. 2.** The general ecological vulnerability maps of China from 2012 to 2014.

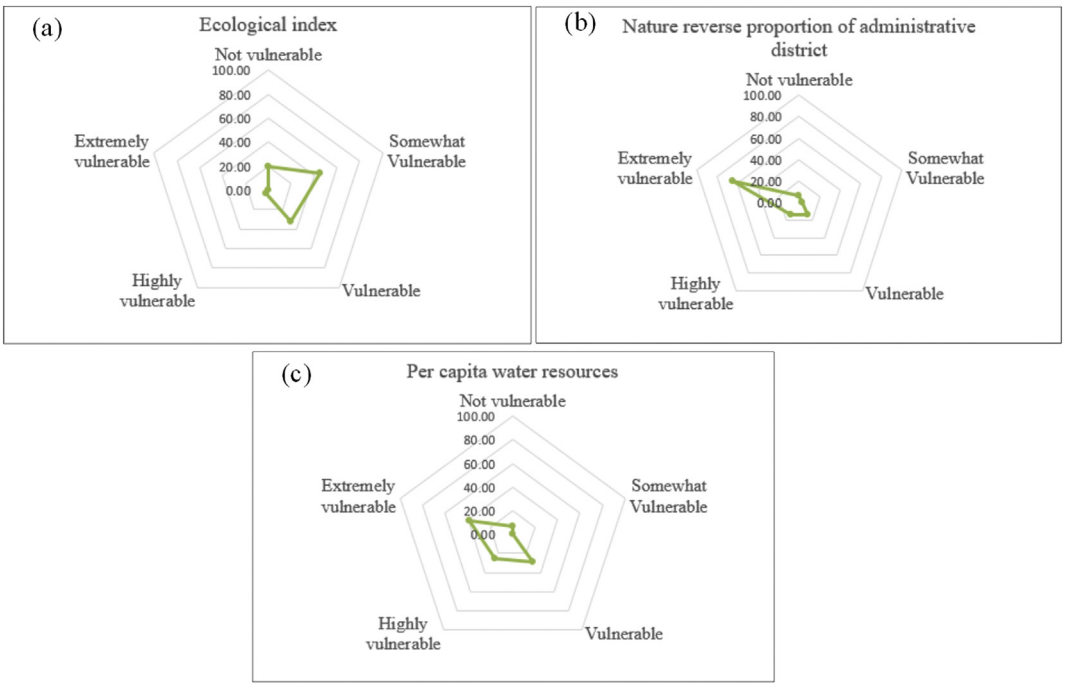


**Fig. 3.** The proportional distribution of ecological situation for 31 provinces in China.

are counted to evaluate their impact on ecological vulnerability. Higher proportional distribution of an indicator dropped in higher vulnerability level means its more impacts on ecological vulnerability and higher proportional distribution in weaker vulnerability indicates its lower impact on the vulnerability results. As the policy making is dependent on the latest ecological situation, only the data in 2014 is analyzed to evaluate sub-parameter impact on ecological vulnerability. More details are presented below.

### 3.2.1. Ecological situation impact

The proportional distribution results of the three sub-parameters for ecological situation impacts in 2014 are shown in Fig. 3. Results show that the sequence of impact from most to least is nature reserve proportion of administrative district, per capita water resources, and ecological index. For ecological index, as presented in Fig. 3(a), the somewhat vulnerable (45.16%) and vulnerable (32.26%) level take up the most proportion in China. Six southern coastal provinces including Zhejiang, Fujian, Jiangxi, Guangdong, Guangxi, and Hainan show the best performance on ecological index with not vulnerable level, but Xinjiang (in the northwest) shows the worst performance with extremely vulnerable level. In Fig. 3(b), the extremely vulnerable proportion for nature reverse proportion of administrative district with 64.52% accounts for a major portion in China. Only Qinghai and Xizang show the best performance at not vulnerable level. Meanwhile, the scores in western provinces are generally lower than that in the northeastern, central, and southern regions. As shown in Fig. 3(c), the proportion distributions of per capita water resources are 6.15%, 32.26%, 32.26%, and 29.03%, respectively for not vulnerable, vulnerable, highly vulnerable, and extremely vulnerable. Xizang and Qinghai still show best performance with not vulnerable degree. In the other provinces, the scores generally decline from northern to southern regions.

### 3.2.2. Ecological infrastructure impact

Fig. 4 presents the proportional distribution results of ecological infrastructure impacts. The order of impact from most to least is pro-environment input intensity, R&D input intensity, PGDP, and innocuous disposal rate of municipal waste. For the pro-environment input intensity, about 90% provinces in China are extremely vulnerable. The general situation for innocuous disposal rate of municipal waste is acceptable with 85% provinces at not vulnerable and somewhat vulnerable level. For the R&D input intensity, scores of some economically developed regions, like Beijing, Tianjin, Shanghai, Jiangsu, and Guangdong, are below 0.4, the other 26 provinces are more than 0.4. The PGDP status is mainly at the extremely vulnerable (48.39%) and highly vulnerable level (19.35).

### 3.2.3. Environmental situation impact

The six sub-parameters of environmental situation impact are illustrated in Fig. 5. From Fig. 5 (a) to (d), it can be seen that the average annual concentrations of $PM_{2.5}$ and $PM_{10}$ are obviously worse than that of $SO_2$ and $NO_2$, and $SO_2$ shows the best performance. The temporal comparison shows that the southern provinces are obviously better than that in the northern provinces. For the $SO_2$ contamination, not vulnerable (61.29%) and somewhat vulnerable (29.03%) level account for the main proportion in China and only Shanxi, Shandong, and Hebei are at vulnerable level. For $NO_2$, the somewhat vulnerable (51.61) and vulnerable level (32.26%) takes the dominant place, and higher vulnerability level are mainly in the central regions and southeastern provinces. For the qualified rate of drinking water, presented in Fig. 5(e), 74.19% and 16.13% of 31 provinces show not vulnerable level and somewhat vulnerable level, respectively. Almost 65% of provinces in China show bad performance in surface water quality as shown in Fig. 5(f). Only Fujian, Jiangxi, Hubei, Hunan, Guangxi, Hainan, Guizhou, Xizang, Gansu, Qinghai, and Xinjiang are at not vulnerable and somewhat vulnerable level.

### 3.2.4. Human health impact

The proportional distribution results of the two sub-parameters for human health impacts in China are shown in Fig. 6. It can be seen that the whole situation of human health in the 31 provinces

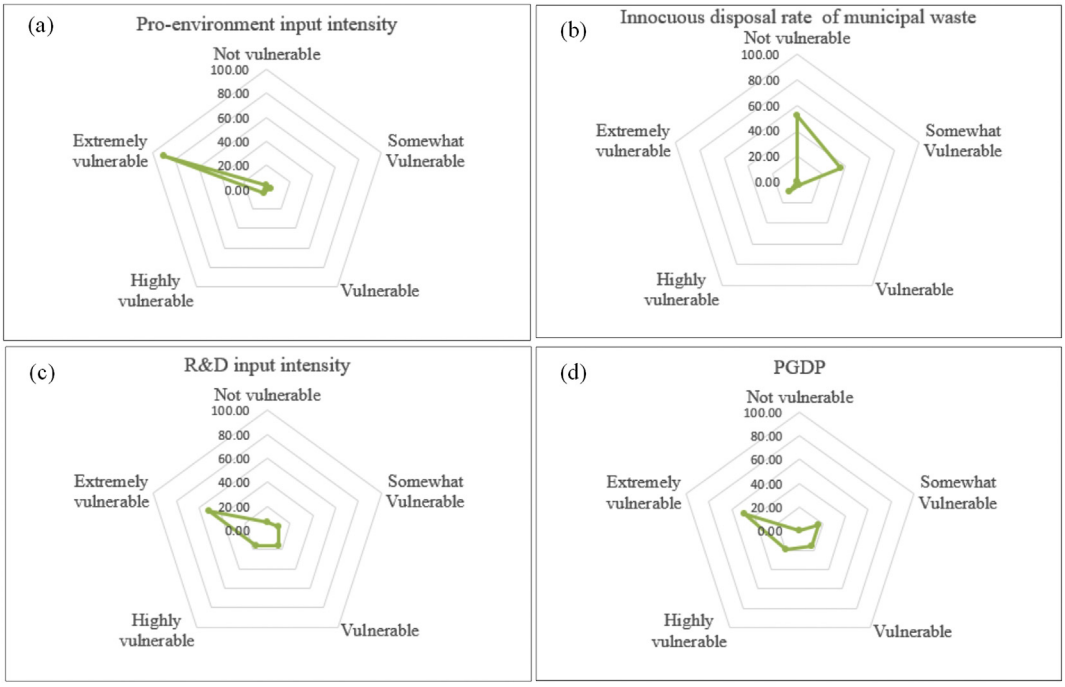


**Fig. 4.** The proportional distribution of ecological infrastructure for 31 provinces in China.

of China are not optimistic and these two parameters both have major impact on ecological vulnerability. For population density in Fig. 6 (a), there are 35.48% and 64.52% of the 31 provinces are highly vulnerable and extremely vulnerable, respectively. The proportion distributions in Fig. 6(b) are 29.03% and 70.97% of vulnerable and highly vulnerable for the percentage of vulnerable groups, respectively.

### 3.3. Implications for ecological conservation and environmental management

#### 3.3.1. Implications for ecological conservation

To give a visual and intuitive support for decision making of ecological conservation, three partitions are proposed according to the five vulnerable classes. Therefore, a zoning map for ecological conservation (Fig. 7) is presented basing on the general ecological vulnerability map in 2014. The three district partitions are presented as following:Ⅰ—Districts for focal protection, Ⅱ—Districts for composite development, and Ⅲ—Districts for strict protection.

(1). Districts for focal protection. These districts consist of the regions with 'not vulnerable' and 'somewhat vulnerable' vulnerability classes. In China, these districts are mainly in the southwestern areas (Xizang and Qinghai) and the southernmost province (Hainan), accounting for 20.64% (approximately 1,974,000 $km^2$) of national territory area of the 31 provinces in China.
(2). Districts for composite development. These districts present the provinces with the vulnerability class of 'vulnerable vulnerability' that appears prominently in the northeastern, central, mid-southern, and southeastern provinces, accounting for 58.14% (approximately 5,560,900 $km^2$) of the territory area.
(3). Districts for strict protection. The provinces with 'highly vulnerable' and 'extremely vulnerable' vulnerability classes generate these districts, lying mainly in the mid-eastern and northwestern provinces with 21.22% of national territory area (approximately 2,029,200 $km^2$) in China.

#### 3.3.2. Implications for environmental management

According to the sub-parameter impact analysis results, it can be seen that the impact factors of ecological vulnerability in China mainly derived from increasing population pressure, exhausted nature resources, extensive economic growth, severe environmental pollution, insufficient environmental protection investment, and accelerating population aging. Therefore, specific environmental management and protection implications are suggested for future policymaking and ecological management in China as follow:

(1) As for ecological situation, most northern and eastern provinces need strict protection on ecological quality. Water resources shortage is a severe phenomenon in 29 provinces of China (except Xizang and Qinghai) and reasonable water utilization management should be urgently built. The target per capita water resources should be 7500 $m^3$/people.
(2) For the pro-environment input, 29 provinces except for Xizang and Qinghai should increase pro-environment input to a percentage at least 2% of GDP.
(3) The general situation of household waste treatment in China is acceptable, but Jilin, Heilongjiang, Gansu, and Xinjiang should especially increase the innocuous disposal rate of municipal waste over 90%.
(4) The R&D investments in southern provinces are more than those provinces in the north. 26 provinces in China still should enhance R&D investment over a percentage with 5% of GDP, except 5 economic developed provinces: Beijing, Tianjin, Shanghai, Jiangsu, and Guangdong.
(5) PGDP: 25 provinces are in the range from early industrial to late industrial stage, except Beijing, Tianjin, Neimongol, Shanghai, Jiangsu, and Zhejiang. Therefore, the economic

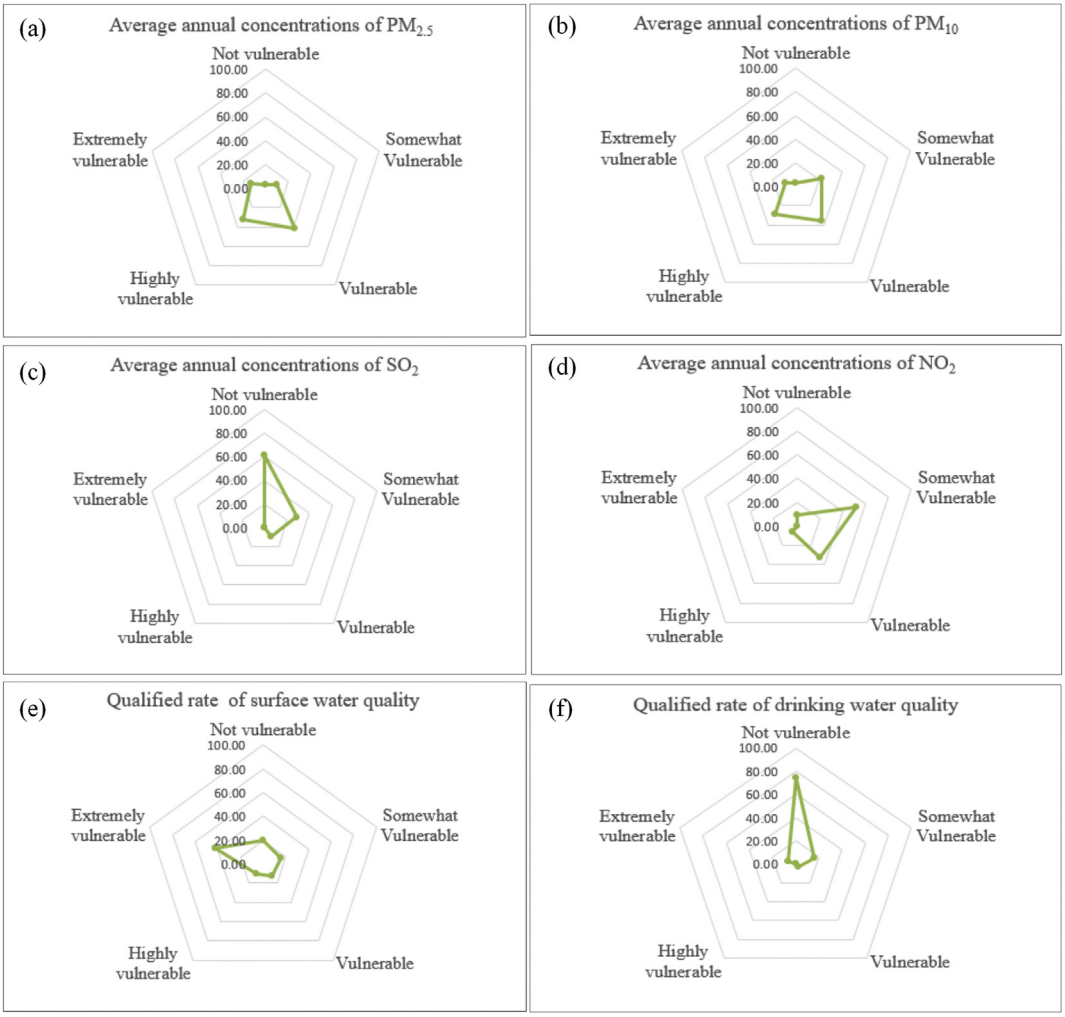


**Fig. 5.** The proportional distribution of environmental situation for 31 provinces in China.

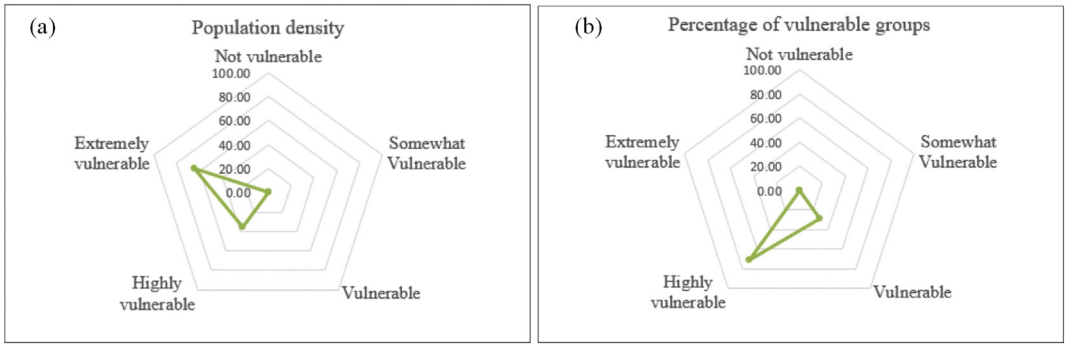


**Fig. 6.** The proportional distribution of human health for 31 provinces of China.

growth of these 25 provinces should change from the extensive growth mode to intensive growth mode.

(6) For atmospheric environment quality control, all the northern provinces should take more regulatory measures to reduce the average annual concentration of $PM_{2.5}$ and $PM_{10}$ down to 35 $\mu g/m^3$ and 70 $\mu g/m^3$ (China ambient air quality standards), respectively, at the first transitional period and then reach to the second and third interim target formulated by WHO Air quality guidelines. Shanxi, Shandong, and Hebei should improve $SO_2$ pollution regulation and reduce the average annual concentration of $SO_2$ to 60 $\mu g/m^3$. Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Shandong, Henan, Chongqing, Shaanxi, and Xinjiang should reinforce $NO_2$ control and keep the average annual concentration of $NO_2$ below 40 $\mu g/m^3$.

(7) In water quality management, most provinces do well in drinking water quality control, but Neimongol, Shanghai, and Ningxia should enhance the qualified rate of drinking water

**Fig. 7.** The zoning map for ecological conservation in China.

quality over 90% in the future environmental protection. Meanwhile, the surface water quality management are not optimistic in China except some western and southern provinces (Fujian, Jiangxi, Hubei, Hunan, Guangxi, Hainan, Guizhou, Xizang, Gansu, Qinghai, and Xinjiang), the other 20 provinces, especially the economic developed area, should make more efforts to strengthen surface water quality improvement and improve the qualified rate of surface water quality over 75%.

(8) For human health, the whole situation for population density and percentage of vulnerable groups of the 31 provinces in China are all very negative. Making an effective and appropriate population government is an urgent and indispensable task the Chinese government.

## 4. Discussions

To evaluate impacts of natural, social, economic, environmental pollution, and human health elements on ecological vulnerability at provincial scale, we used MCDA method with a hierarchical structure to capture the diverse and often incommensurate attribute of ecological vulnerability. The limitation of the hierarchical structure is embodied in non-unique hierarchical representation (Eakin and Bojórquez-Tapia, 2008). As plausible alternative hierarchies can lead to diverse sets of weights that have far-reaching influences in the general ecological vulnerability assessment. The constructed ecological vulnerability framework based on hierarchical structure should be a hermeneutical and heuristic tool for a better understanding of ecological vulnerability. The framework we presented here should be thus considered as the outcome of our best interpretation to select determinants for ecological vulnerability.

Despite the limitation of the constructed framework, our methodology still has five important advantages: firstly, the approach demonstrated the effectiveness in describing the complexity of ecological vulnerability in quantitative and manageable pattern. The application of the AHP to produce attribute weights ensures that the role of each parameter is considered in relation to not only the object concept (ecological vulnerability) but also other parameters in the framework. Secondly, the developed framework is a useful tool because of its flexibility in process, selection of indicators, assessment, and validation. Thirdly, it may benefit ecology and environmental managers to better understand the general impact of various natural and human activities on ecological vulnerability. Fourthly, the developed framework could be applied at up- and down-scaled by national/regional decision-makers according to concrete research situations and data availability. Finally, it's a useful and effective tool that can provide policy-guidance for ecological conservation and environmental management to reduce the ecological vulnerability.

According to the sub-parameter impact analysis, the rank list of influence parameter in China, from most important to least (but still very important), is: pro-environment input intensity, population density, nature reserve proportion of administrative district, percentage of vulnerable groups, R&D input intensity, PGDP, qualified rate of surface water quality, per capita water resources, average annual concentration of $PM_{2.5}$, average annual concentration of $PM_{10}$, average annual concentration of $NO_2$, ecological index,

innocuous disposal rate of municipal waste, average annual concentration of $SO_2$, and qualified rate of drinking water quality. Only the situation of innocuous disposal rate of municipal waste and average annual concentration of $SO_2$ are mainly in not vulnerable and weak vulnerability levels, the other 13 parameters should be strictly controlled and enhanced. The mid- and long-term control target can be decided according to the attribute class presented in Appendix A. Therefore, it can be seen that the constructed ecological vulnerability framework is verified to be effective and helpful for decision-making in policy making and ecology management.

## 5. Conclusions

Evaluating ecological vulnerability is significant for protecting and promoting eco-system stability. This paper presents a first attempt to assess ecological vulnerability at provincial scale and provides a prototype framework that should be helpful for modeling potential impacts of changes in natural, social, economic, environmental pollution, and human health elements on ecological vulnerability. It's also a useful and effective tool that can provide policy-guidance for ecological conservation and environmental management to reduce the ecological vulnerability.

The assessment results of this study confirm the poor ecological vulnerability in China that only 1.32% of the China's population lives in not vulnerable vulnerability ecosystem. A very high percentage (98.68%) of Chinese with 1.34 billion people lives in vulnerable and highly vulnerable area. Meanwhile, spatial disparity exists in China that the central and northwestern provinces show higher ecological vulnerability than the northeastern and southern provinces. The results indicate that increasing population pressure, exhausted nature resources, extensive economic growth, severe environmental pollution, insufficient environmental protection investment, and accelerating population aging are principal influence factors for the ecological vulnerability in China. As these influence factors are also ubiquitous in the eco-system of many other countries all around the world. The presented study in China here could be an implicational research of ecological vulnerability assessment and management for other researchers.

The framework shown in this paper is a hermeneutical and heuristic tool for a better understanding of ecological vulnerability. This study can be replicated at different spatial and temporal scales using context-specific datasets to straightly support ecological managers and government with decision-making. With available robust climate change models, future research might incorporate climate change into the ecological vulnerability framework.

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## Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2017.11.059.

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